# Smartphone Sensor Data Analysis for Human Activity Recognition: A Machine Learning Approach

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## ABSTRACT

Human activity recognition, or HAR for short, is a broad field of study concerned with identifying the specific movement or action of a person based on sensor data. The sensor data may be remotely recorded, such as via video, radar, or other wireless methods. It contains data generated from accelerometers, gyroscopes, and other sensors on smart phones to train supervised predictive models using machine learning (ML) techniques like logistic regression, decision trees, and support vector machines (SVM) to generate a model. These ML techniques can be used to predict the kind of movement being carried out by the person, which is divided into six categories: walking, walking upstairs, walking downstairs, sitting, standing, and laying. Results show that the SVM approach is a promising alternative to activity recognition on smart phones compared to other ML techniques.

**Keywords:** Machine learning, human activity, logistic regression, decision tree, support vector machine.

## 1. INTRODUCTION

Recognizing human activities by means of sensors attached on the body has been widely studied [1-4]. Common activity and functional performance level of a person can be determined by the capability to record and identify distinctive daily activities. In the health care field, initial detection of diseases could be obtained through long term inquiry of human activity or to stimulate people to be physically active and improve their exercise opportunities. As far as physiotherapy, it can help to comprehend if an exercise is been correctly accomplished or even to monitor possible disordered. Security and entertainment are other fields impacted by investigation of human behavior through mobile phone data. Mobile phones were used in police investigations to track suspects and victims [2]. Advancements in the field of medicine have greatly improved our quality of life which is clear in the rise of life expectancy. Rising health-care costs, especially in the treatments of the elderly, have called for cost-cutting measures from various health-care institutes. Technological advancements could contribute significantly in cutting down health-care costs by making the medical staff and the hospital environment more efficient [3].

In the last decade, human activity recognition (HAR) has emerged as a powerful technology with the potential to benefit elderly and differently abled. Simple human activities have been successfully recognized and researched so far. Recognizing complex human activities remain challenging and active research is being carried out in this area. Essentially, activity recognition requires a math model which enables the identification of interest. In general, models can be created using the knowledge of the specialist about the phenomenon which needs shape or by techniques of ML (statistical and neural). An ML model, among other benefits, allows us build models based on with little or no prior knowledge about the task of interest. In this regard, examples of pattern should be captured or available. The purpose of being able to classify what activity a person is undergoing at a given time is to allow computers to provide assistance and guidance to a person prior to or while undertaking a task. The difficulty lies in how diverse our movements are as we perform our day-to-day tasks. There have been many attempts to use the various ML algorithms to accurately classify a person's activity, so much so that Google have created an activity recognition API for developers to embed into their creation of mobile applications. The contribution of this paper as follows, we can determine what is normal and what abnormal activity is for them therefore indicating whether they require attention from facility staff. Innovative approaches to recognize activities of daily living (ADL) are essential input part for development of more interactive human-computer applications. Methods for understanding HAR are developed by interpreting attributes derived from motion, location, physiological signals and environmental information.

The primary goal of HAR is to accurately detect common human activities in real-life settings. Many ML techniques like decision tree, logistic regression, and SVM have been used to predict activities with good accuracy. In this paper, some of these HAR classifier models are applied on a dataset.

## 2. PROPOSED METHOD

### 2.1. MODULES

The activity recognition process is described, containing four main stages.

**Data Collection:** The first step is to collect multivariate time series data from the phone's and the watch's sensors. The sensors are sampled with a constant frequency of 30 Hz. After that, the sliding window approach is utilized for segmentation, where the time series is divided into subsequent windows of fixed duration without inter-window gaps. The sliding window approach does not require preprocessing of the time series and is therefore ideally suited to real-time applications.

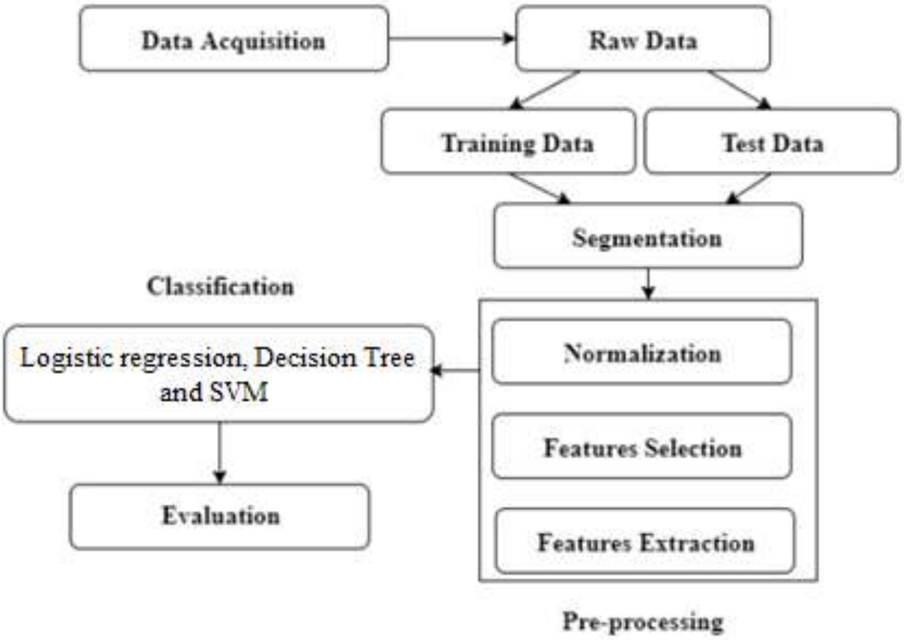


Figure 1: Human activity recognition chain of steps flow chart.

**Preprocessing:** Filtering is performed afterwards to remove noisy values and outliers from the accelerometer time series data, so that it will be appropriate for the feature extraction stage. There are two basic types of filters that are usually used in this step: average filter or median filter. Since the type of noise dealt with here is like the salt and pepper noise found in images, that is, extreme acceleration values that occur in single snapshots scattered throughout the time series. Therefore, a median filter of order 3 (window size) is applied to remove this kind of noise.

**Feature Extraction:** Here, each resulting segment will be summarized by a fixed number of features, i.e., one feature vector per segment. The used features are extracted from both time and frequency domains. Since, many activities have a repetitive nature, i.e., they consist of a set of movements that are done periodically like walking and running. This frequency of repetition, also known as dominant frequency, is a descriptive feature and thus, it has been taken into consideration.

**Standardization:** Since, the time domain features are measured in (m/s 2 ), while the frequency ones in (Hz), therefore, all features should have the same scale for a fair comparison between them, as some classification algorithms use distance metrics. In this step, Z-Score standardization is used, which will transform the attributes to have zero mean and unit variance, and is defined as

$$x_{new} = (x - \mu)/\sigma$$

where μ and σ are the attribute's mean and standard deviation, respectively.


Figure 2: Data flow from smartphone to the laptop.

In this work, six activities were targeted to be detected and recognized. For classification phase, software was developed that applies few supervised classification algorithms models and do comparison between them in term of accuracy and speed factors. The experiments have been carried out on a group of fifteen volunteers aged between 19-35 y. The volunteers performed twelve activities as they have smart phone in their pockets (operating on android). Any activity can be performed for any time duration in any order. Like walking for 30 sec, sitting for 1 min, laying down for 40 sec etc. The acquired data collected from the fifteen subjects with their complete consent and kept indexed as anonymous. By using its embedded accelerometer and gyroscope; 3-axial linear acceleration (for speed and directions) and 3-axial angular velocity (for orientations) were captured at a constant rate of 50Hz along with window segment contains fifteen samples. In the segmentation phase, each segment including fifteen samples alone as a part of the raw data signal was processed and analyzed; then it was compared with the processed and analyzed whole signal segments at once. The compression of handling the whole signal or single segment is based on two factors: Processing time and accuracy. The obtained data set was randomly partitioned into two sets, where 33% of the volunteers were selected to generate the training data and 67% for the data set.

In this phase and as mentioned previously; SVM, is a classifier derived from statistical learning theory introduced. This well-known ML technique minimizes an experimental risk (as a cost function) and at the same time maximizes the margin between the so-called separating hyperplane and the data. In their standard formulation, SVMs are linear classifiers. However, non-linear classification can be achieved through extending SVM by using kernels methods. The key idea of kernels methods is to project the data from the original data space to a high dimensional space called feature space by using a given non-linear kernel functions. Moreover, SVM is a binary classifier; therefore to ensure a multi-class classification, pairwise classifications can be used, which makes it time-consuming especially in case of a large amount of data.

**3. EXPERMENTAL RESULTS**

The accuracy of each model of the 10-fold cross validation was plotted and comparison of the different model was made. Accuracy was plotted against the iteration number of the cross validation. Where accuracy is defined as the ratio of total number prediction that were correct vs the total number of predictions made.

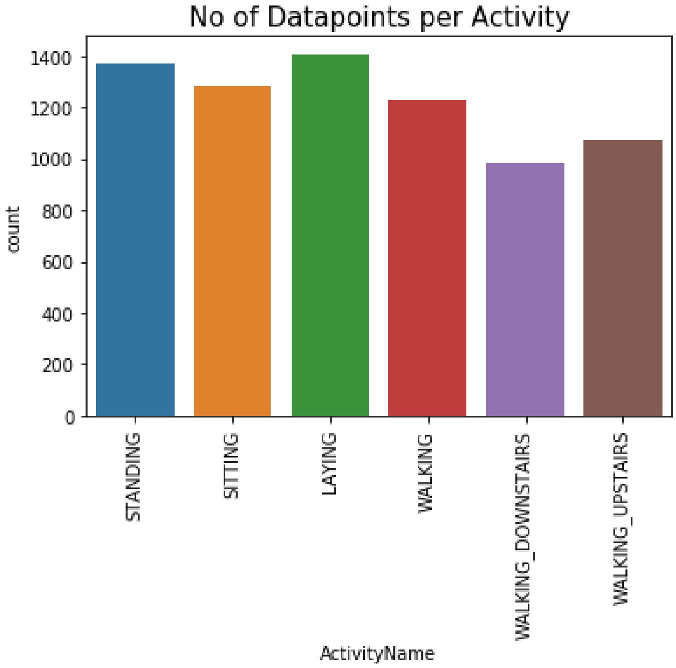


Fig. 3 Classification of the original data set.

As seen in the figure 3 tree model was successful in classifying activity laying completely without any misclassification but had certain degree of misclassification in predicting other activities. Highest number of misclassifications were observed in category standing where it was misclassified 212 times as sitting. The accuracy of each model of the 10-fold cross validation was plotted and comparison of the different model was made. Accuracy was plotted against the iteration number of the cross validation. Where accuracy is defined as the ratio of total number prediction that were correct vs the total number of predictions made. It was observed that the accuracy of the Tree model remained low as compared to the SVM and logistic regression and decision tree model. The comparison of the SVM model and other ML techniques reveal that SVM model is quite superior.

**Comparing all models**

```
In [55]: # print('\n                        Accuracy     Error')
         print('                          ----------   --------')
         print('Logistic Regression : {:.04}%      {:.04}%'.format(log_reg_grid_results['accuracy'] * 100,\
                                                  100-(log_reg_grid_results['accuracy'] * 100)))

         print('Linear SVC          : {:.04}%      {:.04}% '.format(lr_svc_grid_results['accuracy'] * 100,\

                                                       100-(lr_svc_grid_results['accuracy'] * 100)))

         print('rbf SVM classifier  : {:.04}%      {:.04}% '.format(rbf_svm_grid_results['accuracy'] * 100,\
                                                        100-(rbf_svm_grid_results['accuracy'] * 100)))

         print('DecisionTree        : {:.04}%      {:.04}% '.format(dt_grid_results['accuracy'] * 100,\
                                                       100-(dt_grid_results['accuracy'] * 100)))

                      ----------   --------
Logistic Regression : 96.3%        3.699%
Linear SVC          : 96.67%        3.325%
rbf SVM classifier  : 96.27%       3.733%
DecisionTree        : 86.36%       13.64%
```

Fig. 4 shows the plot of accuracy of the models generated during the k fold cross validation.

## 4. CONCLUSION

The researchers at the recent related works at the HAR field; recognized maximum four activities by using 1 to 2 classifiers models along with decent classification accuracy results in their research. While in this research, we managed to expand the number of recognized activities up to six human actions. Meanwhile, four classification models were used to find out the best suitable model for HAR field. In addition, we achieved a particularly good level over the accuracy and time factors as a performance indicator to HAR research quality. From the analysis conducted in this paper out of the 10 cross validation conducted SVM outperformed the other classifiers, whereas the tree model produced poor result throughout. It can be clearly said that SVM model can be effectively utilized when used for activity recognition using the data provided by the accelerometer and gyroscope of a smartphone.

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